Does respondent uncertainty explain framing effects in double bounded contingent valuation?

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Abstract

Many stated preference studies have reported framing effects in responses to valuation questions. This occurs when respondents use irrelevant information contained in a question to help them value the good. We investigate if respondent uncertainty can explain two commonly observed framing effects in contingent valuation studies. Specifically using a double bounded dichotomous choice elicitation format, we investigate anchoring (or starting-point bias) and the shift effect, which may indicate if the method is incentive compatible. Respondent uncertainty is measured using a follow up question that asks respondents their certainty about their valuation. We find evidence that the anchoring effect is stronger for respondents expressing uncertainty about their valuation compared to respondents expressing certainty. The shift effect is significant and negative only for respondents expressing certainty. Our findings suggest that anchoring can be reduced if respondents are certain of their valuation, and that iterative elicitation formats are not incentive compatible.
Keywords: Contingent valuation, heterogeneous framing, respondent certainty

JEL codes: D12, D60,

A Introduction

Stated preference methods are widely applied in many different areas of public decision making, such as the environment, health, and transport. These methods are used to elicit monetary values for non-market goods. Stated preference methods use questionnaires and ask respondents their willingness to pay for goods, such as public goods, that are not traded in the market. Individuals may be uncertain about their willingness to pay because they have no prior consumption experience and are likely to possess only limited information about the good in question.

Individuals may try to cope with their uncertainty about the good by using irrelevant information from the questionnaire, such as the question's phrasing or the structure of possible responses to aid them in providing a valuation of the good (McFadden, 1994). This behaviour is called framing. Framing is problematic in stated preference studies because much of the information presented in the questionnaire is not designed to convey information about the value of the good.

In this study, we connect two areas of research in contingent valuation: respondent certainty and framing effects. We use a data set that combines a post-decision certainty measure with a double bounded dichotomous choice elicitation format. We find that respondents who are uncertain about their willingness to pay are more likely to use irrelevant information when answering the contingent valuation questions.

A number of contingent valuation studies acknowledge that while individuals have preferences for non-market goods, they may not be able to express their willingness to pay for the unfamiliar good with certainty (Ready et al., 1995; Wang, 1997). Li and Mattson (1995) asked respondents to state how uncertainty they were about their willingness to pay on a scale between 0-100%. Respondents were asked this after they had answered the contingent valuation question. Li and Mattson (1995) interpret individuals' responses as a probabilistic judgement about their previous valuation response and they find that uncertain respondents provide noisier answers. Post-decision certainty measures have taken several forms including verbal scales (definitely sure, probably sure), and numerical scales (ranging from 1=very certain to 5=very uncertain, or 1=very certain to 10=very uncertain). In contingent valuation studies, post-decision certainty measures are used to eliminate hypothetical bias by calibrating willingness to pay responsess. Blumenschein et al. (2008) state that willingness to pay can be measured accurately if a post-decision certainty measure is added to the study. Champ et al. (1997) was the first study to compared hypothetical willingness to pay (donate) for a public good with actual donations. They found that hypothetical donations were greater than actual donations, however this difference was eliminated if only very certain respondents were considered in the analysis (respondents were asked their certainty on a 1-10 scale following the hypothetical willingness to pay question). Similar results have been found by Blumenschein et al. (1998, 2001, 2008) and Johannesson et al. (1998, 1999).

The most commonly applied stated preference method is dichotomous choice contingent valuation. However, this provides limited information regarding respondents' true willingness to pay. The initial dichotomous choice contingent valuation question (DC1) can be supplemented with a second dichotomous choice question (DC2) resulting in the double-bounded dichotomous choice (DBDC) format. Responses to DC1 determine the bid offered in DC2. If a respondent states 'yes' in DC1 a higher bid is offered in DC2, and vice versa.

There are two framing effects most frequently associated with the double bounded dichotomous choice format. The first framing effect is anchoring. In this case, responses to DC2 are dependant on the bid offered in DC1 (Cameron and Quiggan, 1994). Herriges and Shogren (1996) propose a model of DBDC data in which respondents combined their prior willingness to pay expressed at DC1 with the bid amount specified in DC1 and form a revised (posterior) willingness to pay, which is the weighted average of both amounts. Herriges and Shogren (1996) find if this effect is ignored then estimated willingness to pay is biased. The second effect is a shift in respondents' answers between the two contingent valuation questions. This shift effect can be either positive or negative. A positive shift represents 'yeah-saying' or acquiesence bias; a tendency for respondents to say 'yes' to any bid amount regardless of their true willingness to pay (Alberini et al., 1997). For example, respondents are more likely to answer 'yes' to follow-up contingent valuation questions when they have answered 'yes' to the initial question. A negative shift can be explained if the elicitation format is not incentive compatible because the second contingent valuation question acts as a signal and influences the respondents' answers (Whitehead, 2002; Carson and Groves, 2007). Carson and Groves (2007) argue that the second bid amount in DBDC creates uncertainty about either the cost of the good (to the respondent), or the quality of the good that will be provided. Carson and Groves (2007) suggest that when DC2 is higher than DC1 respondents interpret this as an attempt by the government (or provider of the good) to raise additional revenue, and a when DC2 is lower than DC1 this signals that a lower quality good, than was described, will be provided. Whitehead (2002) combined both anchoring and shift effects into one econometric model.

Anchoring and the shift effect are both framing effects that occur when respondents use irrelevant information contained in the question frame to aid their decision. Usually when analysing framing effects the researcher has assumed that the effects are constant across the sample. However, just as one does not expect all respondents to hold the same valuation for a good, one may not expect all respondents to 'frame' the contingent valuation exercise in the same manner. For instance, not all respondents will anchor their response to DC2 on the bid presented in DC1, and of those respondents who do anchor the degree of anchoring may differ. Recent studies have developed econometric models that introduced heterogeneity into the framing process (Flachaire et al., 2007;

Aprahamian et al., 2007, 2008). Using monte-carlo simulation, Aprahamian et al. (2007) show that parameter estimates are biased if a homogeneous anchoring model is applied when the true anchoring is heterogenous. Further, Aprahamian et al. (2007), in a study that values a reduction of air pollution using dichotomous choice with open-ended follow-up contingent valuation, find that 25% of respondents do not anchor, 25% of respondents anchor perfectly, and the rest are between these two extreme cases. Similarly, Flachaire et al. (2007) investigate heterogenous anchoring in a DBDC study valuing the French natural park of Camargue. They borrow tools from social psychology to assess respondents' representation of the good, and suggest that respondents who do not have an "elaborated view on the subject" are more likely to anchor. However, Aprahamian et al. (2007) and Flachaire et al. (2007) do not include a shift parameter in their analysis. Aprahamian et al. (2008) using monte-carlo analysis show that spurious shift effects can occur if homogeneous anchoring is assumed when the true anchoring process is heterogeneous. We develop this research by considering that both framing effects (anchoring and shift) are heterogenous, and we use respondents' self-reported certainty as a measure of their susceptibility to framing.

The paper is organized as follows. Section 2 presents the econometric model of heterogeneous framing, which incorporates respondent uncertainty as an explanation for heterogeneity. Section 3 discusses the study design. Section 4 presents and discusses the results. We conclude with recommendations for the use of the contingent valuation method in public decision making in section 5.

B Econometric model

Our model considers four types of heterogeneity resulting from respondent uncertainty. Certain and uncertain respondents may differ with respect to their WTP, the variance of their WTP, the degree of anchoring on the initial bid, and the shift effect induced by the second bid.

Respondent i's uncertainty is modelled through variable U_i. This variable is a categorical level of individual uncertainty; certain or uncertain.[1] We model respondent i's unobserved willingness to pay W_{i1}^* as follows:

$$W_{i1}^* = X_i\beta + U_i\theta + \epsilon_i, \qquad \epsilon_i \sim NID(0, \sigma_i^2) \tag{1}$$

where X_i is a set of respondent characteristics that may be expected to influence willingness to pay. The error terms ϵ_i are Normally and Independently Distributed (NID). Respondent uncertainty can have two effects: First, U_i accounts for a potential shift of respondent's W_{i1}^* due to uncertainty. Second, the variances of certain and uncertain respondents' unobserved willingness to pay, W_{i1}^*, can differ such that

$$\sigma_i = \sigma_c(1 - U_i) + \sigma_u U_i \tag{2}$$

where σ_c^2 and σ_u^2 are the variances of error terms for certain respondents and uncertain respondents, respectively.

In a double-bounded mechanism, W_{i1}^* is not observed, rather we observe responses to an initial bid A_{i1} and a second bid A_{i2}. When the respondent answers the first bid (A_{i1}), their response reveals the value of an indicator variable, $I_i(A_{i1}) = 0$, or 1 ('no' or 'yes') where

$$I_i(A_{i1}) = 1 \quad \text{if } W_{i1}^* \geq A_{i1} \quad \text{and } W_{i1} = 0 \quad \text{otherwise}$$

[1] We restrict what follows to the simple binary case where the respondent is classified as certain or uncertain. Extending the model to consider more than two uncertainty levels is straightforward.

If the respondent answers 'yes' to the initial willingness to pay question, a higher follow-up bid A_{i2} is presented ($A_{i2} > A_{i1}$). Similarly, if the respondent answers 'no' to the initial question a lower follow up bid is presented ($A_{i2} < A_{i1}$). Following Herriges and Shogren (1996), we consider that respondents' willingness to pay is modelled by equation (1). However, if respondents anchor on A_{i1} then their response to the follow-up question is a linear combination of W_{i1}^* and the initial bid A_{i1}. Further a "shift" parameter is added, to account for potential incentive incompatibility induced by the follow-up question or 'yea-saying' behaviour (Whitehead, 2002). Thus, the respondents' unobserved willingness to pay when presented with the follow-up question is defined as:

$$W_{i2} = (1 - \gamma_i)W_{i1}^* + \gamma_i A_{i1} + \delta_i$$

Where γ_i accounts for the anchoring effect (starting-point bias) and lies in the interval $[0, 1]$. The "shift" parameter δ_i accounts for incentive incompatibility or 'yea'-saying. Incentive incompatibility or yea-saying exists if $\delta_i < 0$ or $\delta_i > 0$ respectively. If $\delta_i = 0$ no effect exists.

Both Herriges and Shogren (1996) and Whitehead (2002) assume a constant anchoring parameter across the sample ($\gamma_i = \gamma$). Further, Whitehead (2002) assumes the shift effect to be constant ($\delta_i = \delta$). We allow individuals to differ in their anchoring on the initial bid, as proposed by Aprahamian et al. (2008) and Flachaire et al. (2007). We focus on the case where anchoring differs with respect to respondent's uncertainty. The anchoring parameter is defined as:

$$\gamma_i = \gamma_c(1 - U_i) + \gamma_u U_i \tag{3}$$

where certain respondents and uncertain respondents anchor with a level γ_c and γ_u respectively. Similarly the shift effect δ_i can also differ with respect to respondent's uncertainty:

$$\delta_i = \delta_c(1-U_i) + \delta_u U_i \tag{4}$$

The probabilities of respondents' answers to the first and the second bid are such that

$$\begin{aligned}
P[I_i(A_{i1})=1, I_i(A_{i2})=1] &= P(A_{i2} < W_{i2}) \\
P[I_i(A_{i1})=1, I_i(A_{i2})=0] &= P(A_{i1} < W_{i2} < A_{i2}) \\
P[I_i(A_{i1})=0, I_i(A_{i2})=1] &= P(A_{i2} < W_{i2} < A_{i1}) \\
P[I_i(A_{i1})=0, I_i(A_{i2})=0] &= P(W_{i2} < A_{i2})
\end{aligned}$$

Under the assumption of normally distributed error terms, these probabilities are defined as follows:

$$\begin{aligned}
P(A_{i2} < W_{i2}) &= 1 - \Phi\left[\frac{1}{\sigma_i}\left(\frac{A_{i2}-\gamma_i A_{i1}}{1-\gamma_i} - \mu_i - \delta_i\right)\right] \\
P(A_{i1} < W_{i2} < A_{i2}) &= \Phi\left[\frac{1}{\sigma_i}\left(\frac{A_{i2}-\gamma_i A_{i1}}{1-\gamma_i} - \mu_i - \delta_i\right)\right] - \Phi\left[\frac{A_{i1}-\mu_i}{\sigma_i}\right] \\
P(A_{i2} < W_{i2} < A_{i1}) &= \Phi\left[\frac{A_{i1}-\mu_i}{\sigma_i}\right] - \Phi\left[\frac{1}{\sigma_i}\left(\frac{A_{i2}-\gamma_i A_{i1}}{1-\gamma_i} - \mu_i - \delta_i\right)\right] \\
P(W_{i2} < A_{i2}) &= \Phi\left[\frac{1}{\sigma_i}\left(\frac{A_{i2}-\gamma_i A_{i1}}{1-\gamma_i} - \mu_i - \delta_i\right)\right]
\end{aligned}$$

where $\Phi(.)$ is the standard normal cumulative distribution function, $\mu_i = X_i\beta + U_i\theta$ and σ_i, γ_i and δ_i are given by equations (2), (3) and (4) respectively. We then estimate the model by maximum likelihood using the log-likelihood function

$$\ell = \sum_{i=1}^{n} \Big\{ W_{i1} W_{i2} \log[P(A_{i2} < W_{i2})]$$
$$+ W_{i1}(1 - W_{i2}) \log[P(A_{i1} < W_{i2} < A_{i2})]$$
$$+ (1 - W_{i1}) W_{i2} \log[P(A_{i2} < W_{i2} < A_{i1})]$$
$$+ (1 - W_{i1})(1 - W_{i2}) \log[P(W_{i2} < A_{i2})] \Big\}$$

C Survey design and data

The good being valued in our study is the provision of a national air ambulance service in England and Wales. Air ambulances are part of the emergency services in England and Wales. However, in England and Wales air ambulances are not fully funded by the National Health Service. The level of government funding (from the National Health Service) for the air ambulance service varies across the regions in England and Wales, and in many cases the regional service is supported by donations from the public to a charitable organisation. The data used in this paper elicited willingness to pay from a representative random sample of 1400 members of the public. Respondents were interviewed using computer assisted telephone interview (CATI). Individuals were randomly assigned to one of two payment vehicles (taxation and charitable donation). Both payment vehicles were, and are currently, used to fund the air ambulance service in England and Wales. Respondents' willingness to pay was elicited using a two-stage process. Initially, individuals were asked if they were willing to pay anything each year to ensure the future provision of the air ambulance service. Subsequently, individuals who stated 'yes' entered double bounded dichotomous choice exercise and were randomly assigned an initial bid. Individuals who stated 'no' to the intial question were asked the reasons for their response.

On starting the double bounded dichotomous choice exercise, individuals were told that they would be presented with two valuation questions and that the second valuation question was dependent on their response to the initial valuation question. Individuals were randomly presented with one of five initial bids (A_1): £25 £50, £100, £200, and £300. If a 'yes' ('no') response was given to A_1, respondents were presented with a higher (lower) 'follow up bid' (A_2). Thus the bid amounts presented in A_2 depend on the randomly assigned A_1. The study design gave the following set of bid sequences: £25 ($\bar{A}_2$=£10 and $\underline{A_2}$=£50); £50 (£25,£100); £100 (£50,£200); £200 (£100,£300); £300 (£200,£400).

Air ambulances were introduced fairly recently as part of the emergency services in England and Wales, and they are less frequently used than traditional road ambulances. We expect that familiarity with the air ambulance service will vary across respondents, and familiarity will depend on the use of air ambulances near where respondents live and the fundraising efforts of their regional air ambulance charity. Following A_1 individuals were asked to assess their degree of certainty about their response. Certainty was measured on a 5-point scale (1=very uncertain to 5=very certain). Following the contingent valuation exercise individuals were asked a series of questions about their socioeconomic characteristics.

D Results

The final data set comprises of 690 respondents. Given the objective is to consider framing effects in the DBDC exercise, respondents who stated 'no' to the screening question are not considered further; this reduces the sample size from 1400 to 807. Missing values in major explanatory variables such as income (215 missing) and education (82 missing) further reduce the sample size to 690. Table 1 presents a summary of respondents' characteristics for the initial sample and the sample considered in the analysis.

The proportion of respondents stating 'yes' across the bid amounts is presented in Table 2. A priori expectations, that as the bid level increases the probability of a 'yes' response falls, are fulfilled for all data. For the full sample the proportion of 'yes' responses to A_1 ranged from 80% for £25 to 18% for £300. A similar pattern was observed for the proportion of 'yes' responses to A_2 following a 'no' response (79% - 20%), and following a 'yes' response (36% - 18%). Table 3 presents the 'yes' and 'no' responses for certain and uncertain respondents [2]. Across bounds certain respondents were more likely to state 'yes' to lower bids and less likely to state 'yes' to higher bids. For example, in the case of 'certain' respondents, the probability of 'yes' to the initial bid fell from 80% for £25 to 18% for £300. With 'uncertain' respondents, the probability of 'yes' to the initial bid fell from 59% to 42%.

The econometric results are reported in Table 4. For comparison the first column presents the results for a homogeneous model, as proposed by Whitehead (2002). This model accounts for anchoring and shift effects but not for heterogeneity due to respondents' uncertainty. The second column of Table 4 presents the results for the heterogeneous model presented in section B. The parameter estimates indicate that the questionnaire yielded economically intuitive results. First, the effect of income is significant, at the 5% level, for the highest category (*more than £45k*), implying that respondents who earn more than £45k have an increased probability of stating 'yes' (p =0.007). This is reassuring and provides evidence of theoretical construct validity in the stated preference experiment (Hausman, 1993; Bishop and Woodward, 1995). Second, respondents' mode of transport also has a significant effect: *respondent drives a motorbike* (referent: respondent does not drive any vehicle) has a positive effect, thus high risk road users are willing to pay more for the air ambulance service (p = 0.02). This is logical as high risk road users are more likely to

[2] A respondent is considered to be certain if he states 5 on the certainty scale, otherwise he is considered to be uncertain.

benefit from an air ambulance service and this indicates that valuation estimates are responsive to change in scope (Carson and Mitchell, 1993). Third, the payment vehicle presented to respondents (taxation compared to, the referent, charitable donation) is significant: the probability that respondents state 'yes' increases with a taxation vehicle ($p = 0.001$). This is consistent with the hypothesis that private provision produces an undersupply of public goods, because public good non-excludability permits free riding (Bergstrom et al., 1986).

Respondents' self-reported uncertainty was included as an explanatory variable in the willingness to pay equation. Respondent's uncertainty, θ is not significant in the WTP equation indicating that there is no significant difference between certain and uncertain respondents' prior willingness to pay W_{i1}^*. The variance of W_{i1}^*, σ^2, is however, significantly greater for uncertain respondents when compared with certain respondents ($p = 0.08$). With respect to framing effects, the results indicate that both certain and uncertain respondents are influenced by the first bid. Uncertain respondents have a significantly larger anchoring parameter, $\hat{\gamma}_u = 0.745$, in comparison to certain respondents, $\hat{\gamma}_c = 0.472$ ($p = 0.027$). (The homogeneous model finds a significant anchoring parameter at an intermediate level: $\hat{\gamma} = 0.528$). This implies that uncertain respondents anchor more strongly on the information provided by the initial bid. The 'shift' effect attributed to the follow up question is significantly different across certain and uncertain respondents ($p = 0.005$). Certain respondents are more likely to state 'no' to a follow up question (incentive incompatibility), while the shift effect is insignificant for uncertain respondents. The homogeneous model finds a significant negative shift effect. Finally, the mean WTP for the homogeneous and the heterogeneous equal £139.88 and £108.79 respectively (with standard deviation 85.75 and 58.52).

Conclusion

We investigated if frequently reported framing effects (anchoring and shift effect) were present in the data, and if these were linked to respondent certainty. We reject the hypothesis that certain and uncertain respondents frame the contingent valuation task in the same way. Firstly, uncertain respondents anchor more than certain respondents. This provides empirical evidence that uncertain respondents focus more strongly on the information provided in the contingent valuation scenario. This is inline with the conjecture of both Herriges and Shogren (1996) and Mitchell and Carson (1989) who argue that an uncertain respondent may view the starting bid as providing information about the "correct" WTP value. Our result is also consistent with recent empirical studies, which show that anchoring can depend on individual characteristics (Flachaire et al., 2007; Aprahamian et al., 2007).

Secondly, the shift effect is significantly negative for certain respondents, while it is insignificant for uncertain respondents. This result is consistent with propositions of Carson and Groves (2007), who state that for any contingent valuation elicitation mechanism to be incentive compatible the respondent must believe that their response will influence the provision of the good. Carson and Groves (2007) assert that the second bid amount in the DBDC creates respondent uncertainty either about cost or the quality of the good. They predict that this uncertainty will have a downward effect on mean WTP (this equates to a negative shift parameter in our econometric model). The significant negative shift effect observed for certain respondents, indicates that if respondents are certain of their answer to the initial question, the follow-up question introduces doubt into their mind, and this has the predicted downward effect on WTP. However, the insignificant shift effect observed for uncertain respondents indicates that **if** any additional uncertainty is introduced for these respondents it has no effect on their stated valuation.

Our results indicate that certain respondents are more consistent with the predictions of rational behaviour than uncertain respondents. This is a positive result for the proponents of stated preference methods and implies that by alleviating respondents' preference uncertainty one can reduce the risk of biased and anomalous answers and produce more reliable welfare estimates for public decision making. Our results indicate that self-reported response certainty does not affect respondents' willingness to pay for the good. This finding departs from Cameron (2005)'s findings on willingness to pay for climate change mitigation. Cameron (2005) finds that willingness to pay for climate change mitigation programs depends not only on the anticipated scope of climate change, but also on the individual degree of uncertainty about the scope. In Cameron (2005), respondent's degree of uncertainty is the variance of respondents' subjective probability density functions of average annual temperatures in their region. Thus, respondents' uncertainty has a precise quantitative meaning. This allows Cameron (2005) to estimate a structural model that links respondents' uncertainty to risk aversion.[3] Estimation of this structural form is not possible with measures of self-reported uncertainty, such as those reported in this study, because self-reported uncertainty potentially combines several aspects of respondents' uncertainty.

Although self-reported uncertainty provides interesting information for data analysis, it is a poor proxy for the many underlying sources of uncertainty that respondents may face when completing a contingent valuation exercise: the quality of the service; the continued future provision of the service; the respondent's future need for the service. Contingent valuation research would benefit from the development and introduction of standardized (respondent) uncertainty questions. A relevant theoretical and empirical framework may

[3]This is done by considering that WTP for climate change mitigation programs is an option price that can be estimated by using a particular function form of utility (constant absolute risk aversion, CARA). This is made possible because a CARA utility function only depends on two moments of risk distribution: mean (e.g average annual temperature) and variance (e.g. variance of annual temperatures).

be provided by the literature on eliciting probabilistic expectations (Manski, 2004). These questions will help researchers both to understand, and to model structurally how respondents answer contingent valuation questions. Standardised questions will also provide insights about the type of information that respondents require to ensure less departures from rational behaviour in contingent valuation exercises.

References

Alberini, A., B. Kanninen, and R. T. Carson (1997). Modeling response incentive effects in dichotomous choice contingent valuation data. *Land Economics*, **73**, 309–324.

Aprahamian, F., O. Chanel, and S. Luchini (2007). Modeling starting point bias as unobserved heterogeneity in contingent valuation surveys: An application to air pollution. *American Journal of Agricultural Economics*, **89**, 533–547.

Aprahamian, F., O. Chanel, and S. Luchini (2008). Heterogeneous anchoring and the shift effect in iterative valuation questions. *Resource and Energy Economics*. Forthcoming.

Bateman, I.J., and J. Mawby (2004). First impressions count: Interviewer appearance and information effects in stated preference studies. *Ecological Economics*, **49**, 47–55.

Bergstrom, T., L. Blume, and H. Varian (1986). On the private provision of public goods. *Journal of Public Economics*, **29**, 25–49.

Bishop, R.C and R.T Woodward (1999). Valuation of environmental quality under uncertainty. In D.W. Bromley (Ed.), *The Handbook of Environmental Economics*. Oxford: Basil Blackwell.

Blumenschein, K., G. Blomquist, M. Johannesson, N. Horn, P. Freeman (2008). Eliciting willingness to pay without bias: Evidence from a field experiment. *Economic Journal*, **118**,114–138.

Blumenschein, K., M. Johannesson, G. Blomquist, B. Liljas, and R.M. O'Conor (1998). Experimental results on expressed certainty and hypothetical bias in contingent valuation. *Southern Economic Journal*, **65**, 169–77.

Blumenschein, K., M. Johannesson, K.K. Yokoyama, and P. R. Freeman (2001). Hypothetical versus real willingness to pay in the health care sector: results from a field experiment. *Journal of Health Economics*, **20**, 441–457.

Cameron, T. A. (2005). Individual option prices for climate change mitigation. *Journal of Public Economics*, **89**, 283–301.

Cameron, T.-A. and J. Quiggan (1994). Estimation using contingent valuation data from a "dichotomous choice" with follow-up questionaire. *Journal of Environmenal Economics and Management*, **27**, 218–234.

Carson, R.T. and T. Groves (2007). Incentive and informational properties of preference questions. *Environmental and Resource Economics*, **37**, 181–210.

Carson, R.T. and R.C. Mitchell (1993). The issue of scope in contingent valuation studies. *American Journal of Agricultural Economics*, **75**, 1263–1267.

Champ, P.A., R.C. Bishop, T.C. Brown, and D.W. McCollum (1997). Using donation mechanisms to value nonuse benefits from public goods. *Journal of Environmental Economics and Management*, **33**, 151–162.

Diamond, P.A. and J.A. Hausman (1994). Contingent valuation: Is some number better than no number? *Journal of Economic Perspectives*, **8**, 45–64.

Flachaire, E., G. Hollard, and S. Luchini (2007). Heterogeneous anchoring in dichotomous choice valuation framework. *Louvain Economic Review*, **73**, 369–385.

Hanemann, W.M., Loomis J., and B. Kanninen (1991). Statistical efficiency of double bounded dichotomous choice contingent valuation. *American Journal of Agricultural Economics*, **73**, 1255–1263.

Hausman, J.A. (1993). *Contingent valuation: A critical assessment* Amsterdam: North-Holland Press.

Herriges, J.A. and J.F. Shogren (1996). Starting point bias in dichotomous choice valuation with follow-up questioning. *Journal of Environmental Economics and Management*, **30**, 112–131.

Johannesson, M., Blomquist, G.C., Blumenschein, K., Johansson, P-O., Liljas, B., and O'Conor, R.M. (1999). Calibrating hypothetical willingness to pay responses. *Journal of Risk and Uncertainty*, **8**, 21–32.

Johannesson, M., B. Liljas, and P.-O. Johansson (1998). An experimental comparison of dichotomous choice contingent valuation questions and real purchase decisions. *Applied Economics*, **30**, 643–47.

Li, C.-Z. and L. Mattson (1995). Discrete choice under preference uncertainty: An inproved structural model for contingent valuation. *Journal of Environmental Economics and Management*, **28**, 256–269.

Manski, C. (2004). Measuring expectations. *Econometrica*, **72**, 1329–1376.

McFadden, D. (1994). Contingent valuation and social choice. *American Journal of Agricultural Economics*, **76**, 689–708.

Mitchell, R.C. and T. Carson, R. (1989). *Using Surveys to Value Public Goods : The contingent Valuation Method.* Washington D.C.: Resources for the Future.

Ready, R.C., J.C. Whitehead, and G. Blomquist (1995). Contingent valuation when respondents are ambivalent. *Journal of Environmental Economics and Management*, **29**, 181–196.

Wang, H. (1997). Treatment of don't know responses in contingent valuation surveys: A random valuation model. *Journal of Environmental Economics and Management*, **32**, 219–232.

Whitehead, J. C. (2002). Incentive incompatibility and starting-point bias in iterative valuation questions. *Land Economics*, **78**, 285–297.

Variable	Description	Missing Values	Subsample $n = 690$		Initial sample $n = 1400$	
			mean	sd	mean	sd
TAX	Payment vehicle is *Tax*	0	0.530	0.249	0.49	0.250
MALE	Male	0	0.527	0.249	0.485	0.250
Age		0				
AGE1	Between 18 and 29		0.191	0.155	0.184	0.150
AGE2	Between 30 and 44		0.354	0.229	0.304	0.211
AGE3	Between 45 and 64		0.313	0.215	0.308	0.213
AGE4	Between 65 and 74		0.103	0.092	0.141	0.121
AGE5	More than 75		0.039	0.038	0.063	0.059
Income		215				
INCOME1	Less than £15k		0.179	0.233	0.302	0.211
INCOME2	£25-35k		0.239	0.182	0.233	0.179
INCOME3	£25-35k		0.190	0.153	0.173	0.143
INCOME4	£35-45k		0.139	0.120	0.121	0.106
INCOME5	More than £45k		0.199	0.159	0.171	0.142
Education		82				
EDUC1	No formal		0.092	0.102	0.146	0.124
EDUC2	Up to O level		0.294	0.208	0.299	0.210
EDUC3	A level and Further educ		0.223	0.173	0.214	0.169
EDUC4	Higher educ		0.380	0.235	0.341	0.225
Household composition		5				
NCHILD	# of children in the hhold		0.678	1.039	0.601	0.994
NADULT	# of adults in the hhold		2.071	0.878	1.998	0.890
Place of residence		0				
URBAN1	Middle of a town or city		0.255	0.190	0.269	0.196
URBAN2	In a suburb		0.265	0.195	0.296	0.209
COUNTRY1	Edge of the countryside		0.326	0.220	0.297	0.119
COUNTRY2	Middle of the countryside		0.154	0.130	0.138	0.209
Vehicle		5				
CAR	Respondent drives a car		0.801	0.159	0.740	0.193
MBIKE	Respondent drives a motorbike		0.051	0.048	0.035	0.034
TRUCK	Respondent drives a van or truck		0.036	0.035	0.028	0.027
Respondent's uncertainty						
UCC1	Respondents declares that he his uncertain about his WTP response		0.184	0.150	*na*	*na*

Table 1: Descriptives statistics for the whole sample ($n = 1400$) and the subsample ($n = 690$)

Initial Bid	Answer to the First bid		Second Bid	Answer to the second bid	
£25	*Yes*	112 ($p_y = 0.77$)	£50	*Yes*	40 ($p_y\|_y = 0.36$)
				No	72 ($p_n\|_y = 0.64$)
	No	33 ($p_n = 0.23$)	£10	*Yes*	26 ($p_y\|_n = 0.79$)
				No	7 ($p_n\|_n = 0.21$)
£50	*Yes*	85 ($p_y = 0.70$)	£25	*Yes*	28 ($p_y\|_y = 0.33$)
				No	57 ($p_n\|_y = 0.67$)
	No	37 ($p_n = 0.30$)	£100	*Yes*	25 ($p_y\|_n = 0.68$)
				No	12 ($p_n\|_n = 0.32$)
£100	*Yes*	81 ($p_y = 0.56$)	£50	*Yes*	19 ($p_y\|_y = 0.23$)
				No	62 ($p_n\|_y = 0.77$)
	No	63 ($p_n = 0.44$)	£200	*Yes*	37 ($p_y\|_n = 0.59$)
				No	26 ($p_n\|_n = 0.41$)
£200	*Yes*	49 ($p_y = 0.37$)	£100	*Yes*	11 ($p_y\|_y = 0.22$)
				No	38 ($p_n\|_y = 0.78$)
	No	85 ($p_n = 0.63$)	£300	*Yes*	36 ($p_y\|_n = 0.42$)
				No	49 ($p_n\|_n = 0.58$)
£300	*Yes*	33 ($p_y = 0.23$)	£200	*Yes*	6 ($p_y\|_y = 0.18$)
				No	27 ($p_n\|_y = 0.82$)
	No	112 ($p_n = 0.77$)	£400	*Yes*	23 ($p_y\|_n = 0.20$)
				No	89 ($p_n\|_n = 0.80$)

Table 2: WTP responses

First bid (£)	Answers to the first bid	
	Certain Respondents	Uncertain Respondents
25	yes 99 (80%)	yes 13 (59%)
	no 24 (20%)	no 9 (41%)
50	yes 74 (75%)	yes 11 (49%)
	no 25 (25%)	no 12 (51%)
100	yes 68 (59%)	yes 13 (46%)
	no 48 (41%)	no 15 (54%)
200	yes 38 (35%)	yes 11 (39%)
	no 68 (65%)	no 17 (61%)
300	yes 22 (18%)	yes 11 (42%)
	no 97 (82%)	no 15 (58%)

Table 3: WTP responses to the first bid for certain and uncertain respondents

Variable	Homogeneous model		Heterogeneous model	
	Parameter estimate	(p-value)	Parameter estimate	(p-value)
Constant	21.28	(.559)	11.41	(.757)
Payment vehicle is *Tax*	81.49	(<.001)	80.24	(<.001)
Male	21.74	(.117)	21.35	(.121)
Age				
Between 30 and 44	11.52	(.580)	15.68	(.450)
Between 45 and 64	4.40	(.830)	8.29	(.688)
Between 65 and 74	15.59	(.596)	24.57	(.405)
More than 75	-76.61	(.059)	-52.85	(.182)
Income				
£15-25k	30.56	(.145)	34.50	(.099)
£25-35k	26.23	(.264)	30.72	(.189)
£35-45k	24.59	(.337)	24.04	(.345)
More than £45k	64.15	(.010)	67.08	(.007)
Education				
Up to o level	18.15	(.473)	21.52	(.396)
Further educ	16.81	(.528)	25.22	(.346)
Higher educ	30.86	(.229)	32.20	(.213)
# of childs in the hhold	-1.99	(.783)	-3.94	(.588)
# of adults in the hhold	0.94	(.910)	2.40	(.776)
Place of residence				
In a suburb	-0.23	(.990)	0.85	(.963)
Edge of the countryside	5.65	(.759)	3.84	(.835)
Middle of the countryside	19.82	(.374)	18.41	(.412)
Respondent drives a car	-35.59	(.052)	-33.27	(.070)
Respondent drives a motorbike	79.13	(.015)	76.32	(.020)
Respondent drives a van or truck	17.99	(.637)	19.57	(.626)
Mean effect of respondent's uncertainty				
Uncertain respondents: $\hat{\theta}$	-	-	-24.16	(.342)
Variance of error terms				
Homogeneous variance ($\sigma_i = \hat{\sigma}$)	157.46	(<.001)	-	-
Certain Respondents: $\hat{\sigma}_c$			146.74	(<.001)
Uncertain respondents: $\hat{\sigma}_u$			231.92	(<.001)
Anchoring				
Homogeneous anchoring ($\gamma_i = \hat{\gamma}$)	0.528	(<0.001)	-	-
Certain respondents: $\hat{\gamma}_c$	-	-	0.472	(.007)
Uncertain respondents: $\hat{\gamma}_u$	-	-	0.745	(<0.001)
Shift effect				
Homogeneous shift ($\delta_i = \hat{\delta}$)	-4.72	(0.001)	-	-
Certain respondents: $\hat{\delta}_c$	-	-	-6.23	(<0.001)
Uncertain respondents: $\hat{\delta}_u$	-	-	1.09	(0.755)
loglikelihood $\hat{\ell}$	943.44		931.64	
Mean WTP	139.88		108.79	
Standard deviation of Mean WTP	85.75		58.52	

Table 4: Econometric results ($n = 690$)